Optimizing Robotic Team Performance with Probabilistic Model Checking

Software Engineering Institute Carnegie Mellon University Pittsburgh, PA 15213

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October 22nd, 2014



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1. REPORT DATE 22 OCT 2014				3. DATES COVERED		
4. TITLE AND SUBTITLE				5a. CONTRACT NUMBER		
Optimizing Robotic Team Performance with Probabilistic Model				5b. GRANT NUMBER		
Checking 6. AUTHOR(S) Kyle /David S.				5c. PROGRAM ELEMENT NUMBER		
				5d. PROJECT NUMBER		
				5e. TASK NUMBER		
				5f. WORK UNIT NUMBER		
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Software Engineering Institute Carnegie Mellon University Pittsburgh, PA 15213				8. PERFORMING ORGANIZATION REPORT NUMBER		
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)				10. SPONSOR/MONITOR'S ACRONYM(S)		
				11. SPONSOR/MONITOR'S REPORT NUMBER(S)		
12. DISTRIBUTION/AVAIL Approved for publ	LABILITY STATEMENT ic release, distributi	on unlimited.				
13. SUPPLEMENTARY NO	OTES					
14. ABSTRACT						
15. SUBJECT TERMS						
16. SECURITY CLASSIFIC	CATION OF:		17. LIMITATION OF	18. NUMBER	19a. NAME OF	
a. REPORT unclassified	b. ABSTRACT unclassified	c. THIS PAGE unclassified	SAR	19	RESPONSIBLE PERSON	
a. REPORT	b. ABSTRACT		ABSTRACT SAR	OF PAGES 19	RESPONSIBLE PERS	

Report Documentation Page

Form Approved OMB No. 0704-0188

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This material is based upon work funded and supported by the Department of Defense under Contract No. FA8721-05-C-0003 with Carnegie Mellon University for the operation of the Software Engineering Institute, a federally funded research and development center.

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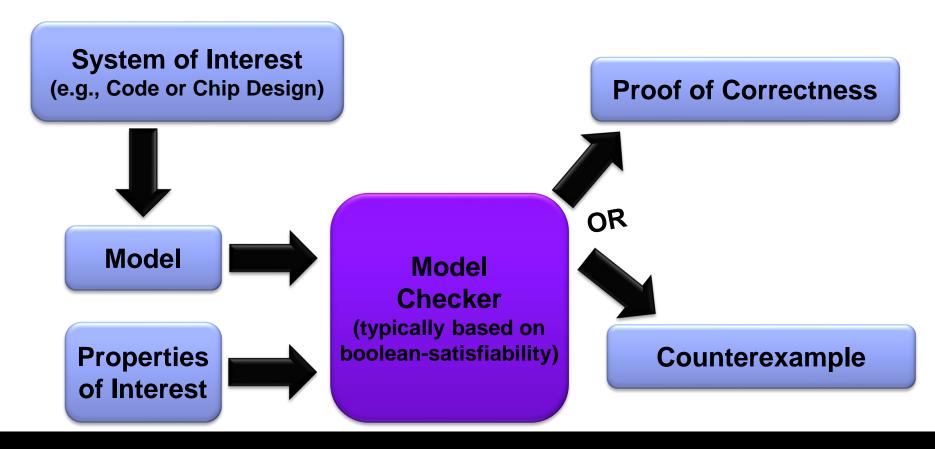
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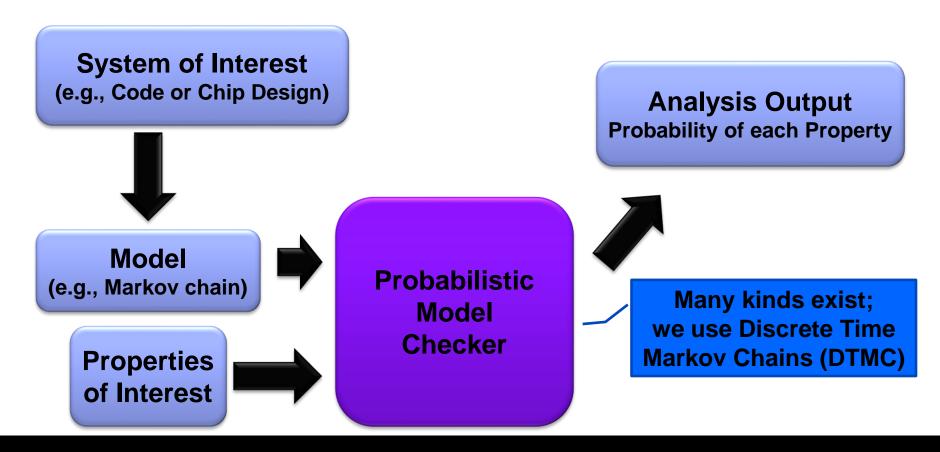
Model Checking

Pentium floating point bug (1995): inspired Intel to model check chips Now being applied to software, as well



Probabilistic Model Checking

Model Checking is purely boolean; a property is true or false. For some systems, we want probabilities



DTMCs and Multi-Agent Robotic Systems

Benefits:

- 1. Performance vs physics-based simulation
- 2. Exact results. Given a model, probabilities are calculated exactly

Essential problems:

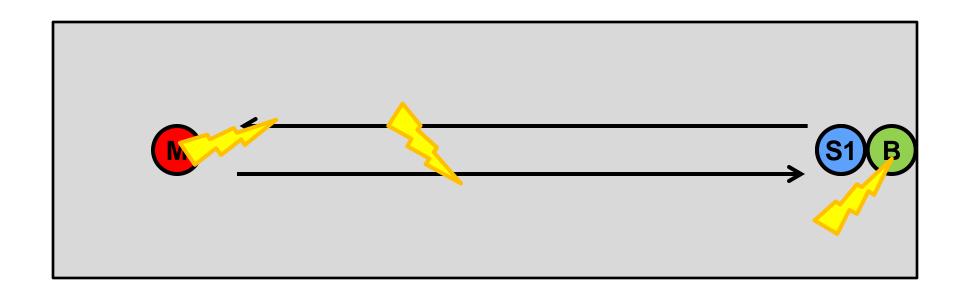
- 1. Modelling physical systems is difficult
 - Can't just extract from a design or program code; must observe system to model it
 - Physical systems are continuous. Probabilistic Model Checking relies on discrete states
 - Given an imperfect model based on finite observations, how does that impact predictions?
- 2. Robots interact. Modelling an entire system of multiple robots is hard.

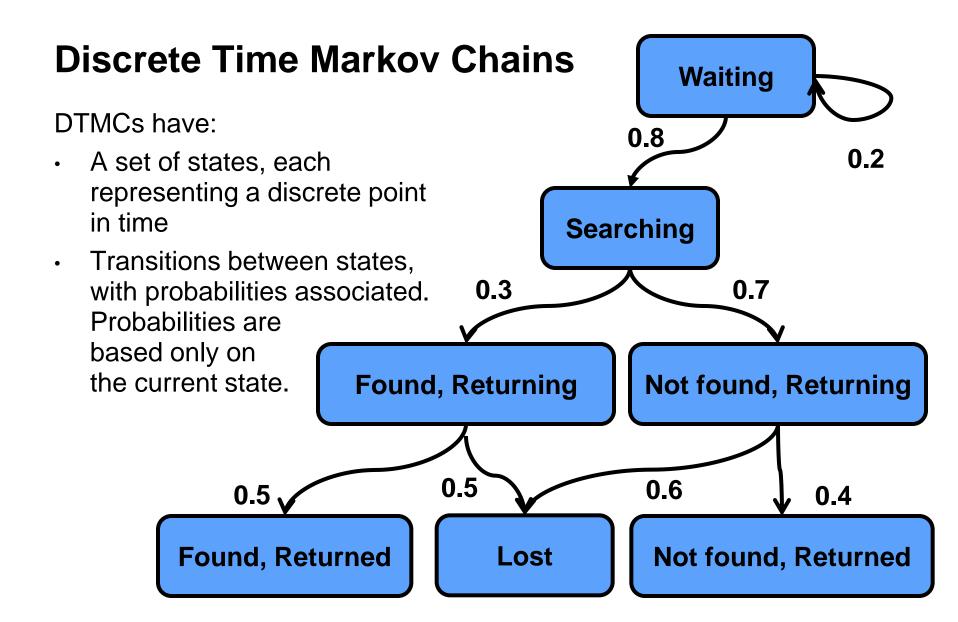
Our Contributions

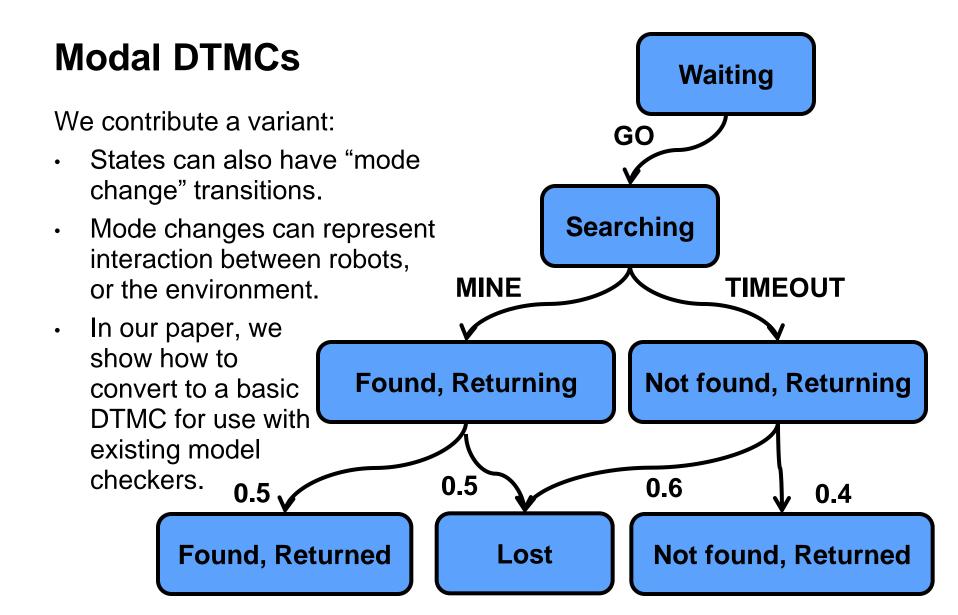
- Model robots individually:
 - observe and measure individual behavior
 - 2. discretize observations in time and space, create Markov models
 - 3. compose these models into a Markov model of the whole system
- 2. Use known statistical error on the measurements made of the individual robots to produce estimates of error of the outputs of model checking the whole system.

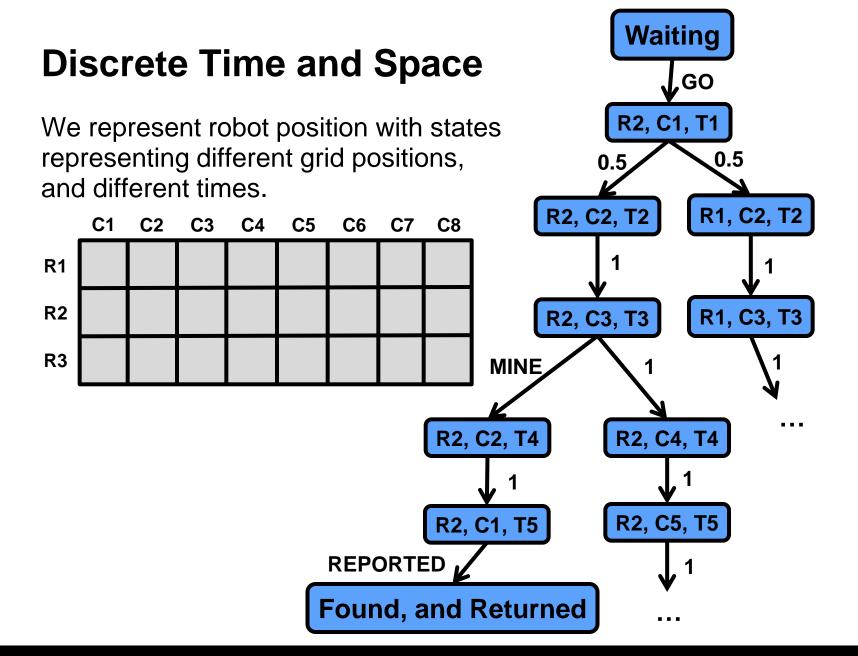
Scenario

For our experiments, and as an illustration, we imagine a mine sweeping scenario. Objective: find a mine/IED in a constrained space (i.e., a drainage culvert under a road).









Composing Modal DTMCs

- Modal DTMCs allow us to model individual robots, then easily compose them together.
- To create an individual model:
 - 1. Run the robots individually, with pre-planned mode changes
 - 2. Observe the robot's behavior
 - 3. Create a Modal DTMC with transition probabilities based on observation, and mode changes as pre-planned
- Then, collect the individual modal DTMCs into a whole-system modal DTMC, and convert it to a non-modal DTMC
- Details of this construction, and correctness proof, are in the paper.

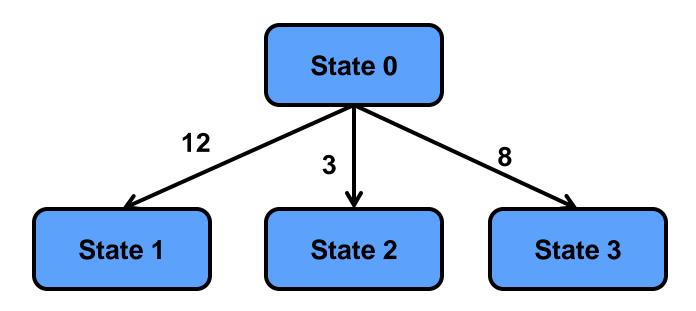
Error Estimation

- Probabilistic Model Checking itself has no error; given a model, it finds exact probabilities.
- However, modeling a robotic system will certainly not be perfect.
- Many kinds of error might appear causing a model to not reflect reality. We looked at handling one: the statistical errors due to observing the individual robots only a finite number of times.
- To examine this specific kind of error, we assume:
 - That the system can be fully described by a DTMC
 - That we have figured out the states of that DTMC
 - But the transition probabilities are observed over the course of finite trials

Dirichlet-based Distribution of DTMCs

To analyze error, we create a random distribution of DTMCs.

For each transition, we use the counts of the times that transition was observed to describe the Dirichlet distribution of transition probabilities for that state, which includes a variance which shrinks with more observations.



Model Checking a distribution of DTMCs

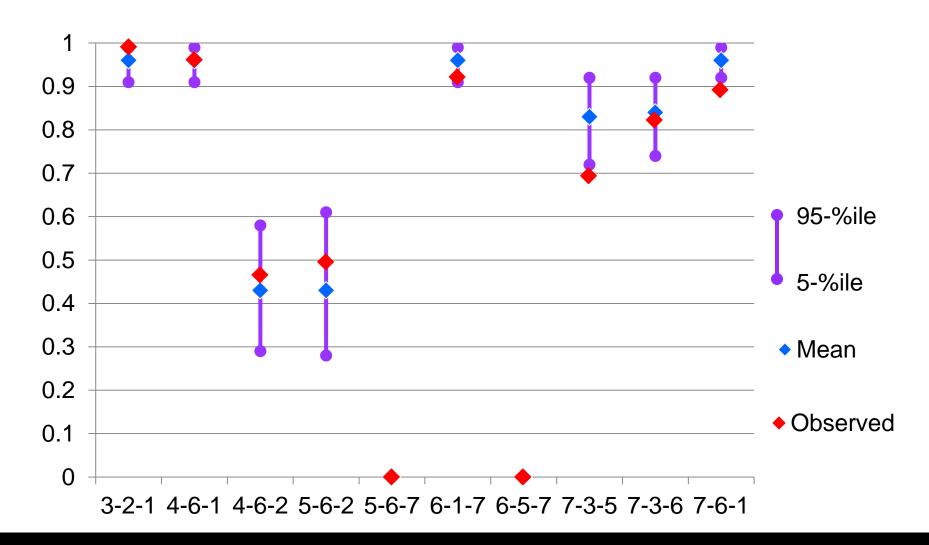
We randomly generate a large number of DTMCs State 0 from the distribution we created. We model check each DTMC, which gives State 1 State 3 State 2 us probabilities for our properties of interest. This gives us a mean and standard deviation for those outputs. State 0 State 0 0.38 State 0 0.32 State 3 0.52 0.35 State 3 0.13 State 2 State 3 State 1



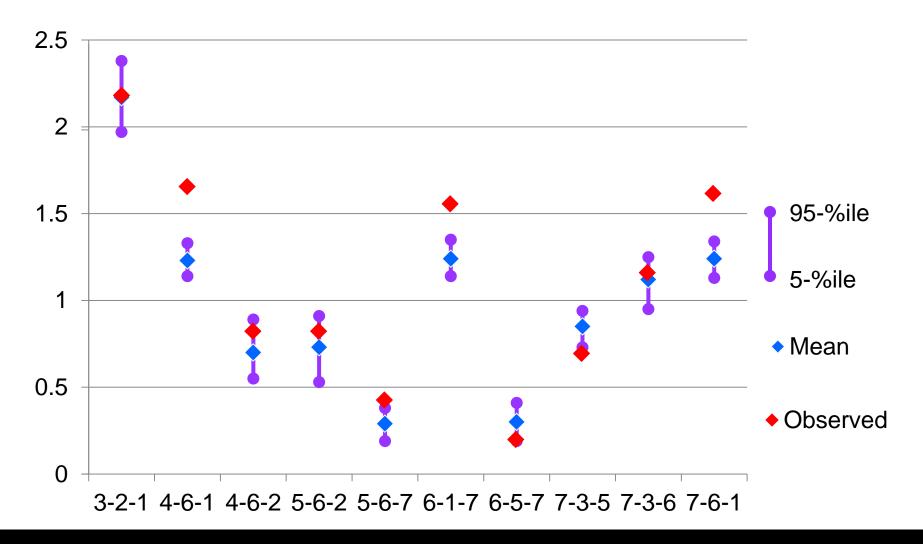
Experiment

- Used the simulator V-REP, with Kilobot models based on observations of real Kilobots
- Simulated Kilobots individually, used observations to create models for various team configurations (using Modal DTMCs), and predicted outcomes, using our Dirichlet sampling technique. Our metrics:
 - Probability base learns of mine (SUCCESS)
 - Expected number of bots that return to base (RETURNED)
- Simulated those teams in V-REP, and compared those outcomes to predicted outcomes.

Experiment Results – SUCCESS metric



Experiment Results – RETURNED metric





Questions?

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